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An Intercomparison Study on Models of Sensible Heat Flux over Partial Canopy Surfaces with Remotely Sensed Surface Temperature

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Using remotely sensed surface temperature to estimate the sensible heat flux over partial canopy covered surfaces, one faces the problem of how the bare soil and plant foliage temperatures contributing to the radiometric surface temperature are related to the turbulent transport of sensible heat across the surface–atmosphere interface. To solve this problem, several sensible heat models, using radiometric surface temperature, have appeared in the literature. In this study, using the observational data from three interdisciplinary field experiments [the First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE), Monsoon '90 and Washita '92], the performance of four models using average values of their parameters in predicting land surface sensible heat flux was evaluated. By analyzing the sensitivity of the models to common parameters and input variables, reasons for differences in the performances of the models and the potential to improve the agreement with observations have been ascertained. From the comparisons of modeled versus measured sensible heat flux for the different surfaces, the dual-source model in Norman et al. (1995) had the best agreement with its mean absolute percent difference (MAPD) values being similar to the observational accuracy (i.e., ~ 20%). From the sensitivity analysis the model appears to have the greatest potential for operational applications since it requires relatively few parameters and is not very sensitive to the uncertainty in most of the model parameters. The single-source models in Kustas et al. (1989) and Troufleau et al. (1996) require accurate estimates of the surface roughness z_{0m} and empirical relationships to account for differences between aerodynamic and radiometric temperature. Therefore, it may be difficult to improve their performance without some independent means of estimating the empirical coefficients and a reliable method for determining z_{0m}. Estimates from the dual-source model in Lhomme et al. (1994) tend to produce the largest scatter with the observations. This may be related to the fact that the model is more sensitive to variations in most of the parameters common in dual-source models. In addition, its response to high surface–air temperature differences in the sensitivity analysis differs from all other models. Therefore, it may be more difficult to obtain reliable estimates from this model on an operational basis.

INTRODUCTION

One of the major difficulties in using remotely sensed surface temperature to estimate the land surface sensible heat flux is accounting for the influence of canopy architecture, fractional cover, sensor view, and solar zenith angles on the observations. These difficulties become extreme for partial canopy covered surfaces, where one faces the problem of how the bare soil and plant foliage temperatures contributing to the radiometric surface temperature are related to the turbulent transport of sensible heat flux across the surface–atmosphere interface. Because of these complexities, some studies have concluded that the use of radiometric surface temperature for predicting the surface sensible heat flux density may not be feasible with an acceptable level of accuracy (e.g., Hall et al., 1992). However, several sensible heat flux models, using radiometric

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Table 1. Sensible Heat Flux Models Using Radiometric Surface Temperature

Model No.	*Name*	*Type*	*Reference*
1	K1	Single-source	Kustas et al., 1989
2	L1	Single-source	Troufleau et al., 1995
3	L2	Dual-source	Lhomme et al., 1994
4	N2	Dual-source	Norman et al., 1995

surface temperature, have given acceptable results. Examples include the single-source models of Kustas et al. (1989) and Troufleau et al. (1996), and the dual-source (two-layer) models of Lhomme et al. (1994) and Norman et al. (1995). Some studies have investigated the utility of one or two of these models (e.g., Stewart et al., 1994; Kustas et al., 1994; Blyth and Dolman, 1995; Kustas et al., 1995). However, few studies have compared the performance and evaluated the applicability of all these models to different landscapes. In this work, we examine the performance of the four sensible heat flux models listed in Table 1, with observational data from the three different field experiments, namely, the First ISLSCP (International Land-Surface Climatology Project) Field Experiment (FIFE), Monsoon '90, and Washita '92. A sensitivity analysis of the different models is performed by assuming a ± 10% uncertainty in model parameters. The results improve our understanding of why the models performed differently with the various data sets, and which model parameterizations strongly influence their performance.

MODEL OVERVIEW

Table 1 is a list of the models using radiometric surface temperature, which will be examined. The names are assigned to the models for convenience in the later referencing. Detailed descriptions of the models are given in the references listed in Table 1. The following is a brief overview of the different models.

Figure 1 schematically demonstrates the resistance networks of the single-source models (K1 and L1) and the dual-source models (L2 and N2). The single-source models treat the whole surface as a single source of the sensible heat transported to the overlying atmosphere while the dual-source models separate the bare soil and plant foliage composing the surface as two different sources of the sensible heat.

There is another form of the N2 model which treats the soil and the plant canopy as parallel sources, rather than the form shown in Figure 1, which treats the soil and the canopy as series sources of the sensible heat (Norman et al., 1995). The performance of the parallel-source form of the N2 model with all the data sets used in this study are very similar to the series-source form. Therefore, only the results of the series-source form of the N2 model will be presented in this article.

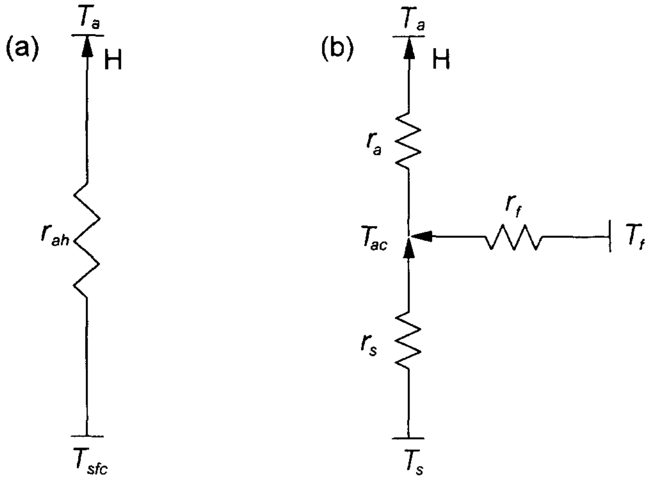

Figure 1. Schematic diagram of (a) single-source and (b) dual-source models of sensible heat flux.

Mathematically, the single-source models (K1 and L1) estimate sensible heat flux H as

$$H = \rho c_p \frac{T_{sfc} - T_a}{r_{ah}}, \tag{1}$$

where ρc_p is the volumetric heat capacity of air, T_{sfc} is a surface temperature, T_a is the reference height air temperature, and r_{ah} is the aerodynamic resistance to sensible heat transport from the surface to the reference height. r_{ah} is computed as follows:

$$r_{ah} = \frac{1}{ku_*}\left[\ln\left(\frac{z - d_0}{z_{0h}}\right) - \psi_h\right], \tag{2}$$

where k is von Karman's constant (0.4), $u_* = ku/[\ln\{(z - d_0)/z_{0m}\} - \psi_m]$ is the friction velocity, d_0 is the displacement height, z_{0m} and z_{0h} are the roughness of the surface for momentum and heat, ψ_m and ψ_h are the stability corrections for momentum and heat, and u is the wind speed observed at the reference height z.

The K1 model assumes that $T_{sfc} = T_{rad}$, $z_{0h} = z_{0m}$ exp $[-(kB^{-1})]$, where T_{rad} is the radiometric surface temperature, kB^{-1} was originally a parameter that accounted for difference in momentum and heat exchanges at the surface (Brutsaert, 1982), and is estimated using the following empirical formula introduced by Kustas et al. (1989):

$$kB^{-1} = s_{kB}\, u(T_{rad} - T_a). \tag{3}$$

The value of the coefficient s_{kB} is observed to vary between 0.05 and 0.25 with some studies suggesting that s_{kB} should be related to the magnitude of H (Troufleau et al., 1996; Kustas et al., 1995). An average value of 0.15 was used in this analysis. Using kB^{-1}, Eq. (2) can be rewritten as $r_{ah} = r_a + r_{ex}$, where $r_a = (1/ku_*[\ln(z - d_0)/z_{0m}) - \psi_h]$ is the aerodynamic resistance for heat without considering the difference between z_{0h} and z_{0m}, and $r_{ex} = (1 / ku_*)(kB^{-1})$ is an excess resistance accounting for the difference between z_{0h} and z_{0m}. Thus for the K1 model, Eq. (1) is rewritten as (Stewart et al., 1994)

$$H = \rho c_p \frac{T_{rad} - T_a}{r_a + r_{ex}}. \tag{4}$$

The L1 model assumes that $T_{sfc} = T_{rad} - \delta T$, $r_{ah} = r_a$, where δT is estimated as

$$\delta T = \alpha(T_{rad} - T_a) + \beta \tag{5}$$

with α and β being empirical coefficients determined from experimental data (Troufleau et al., 1996). Thus for the L1 model, Eq. (1) is rewritten as:

$$H = \rho c_p \frac{(T_{rad} - T_a) - \delta T}{r_a}. \tag{6}$$

The values of α and β are likely to vary with vegetation and surface type as shown by Troufleau et al.. (1995). Using various experimental data sets, a preliminary analysis indicated that the relationship between α (with β set to be zero) and vegetation parameters, such as leaf area index (LAI), described in Troufleau et al. (1995), also varies with surface type. This implies that methods to adjust the values of α and β *a priori* may be difficult to implement in practice. In this analysis, the average values of α and β provided in Troufleau et al. (1996) were used, that is, $\alpha = 0.8$ and $\beta = -0.5$.

The dual-source models (L2 and N2) estimate sensible heat flux H as

$$H = \rho c_p \frac{T_{ac} - T_a}{r_a} = \rho c_p \frac{T_f - T_{ac}}{r_f} + \rho c_p \frac{T_s - T_{ac}}{r_s}, \tag{7}$$

where r_f is the resistance of the leaf boundary layer, r_s is the resistance of the air layer above the soil surface, and T_{ac}, T_f and T_s are, respectively, the temperature of the air within the canopy, the foliage, and the bare soil surface. The three temperatures are usually unknown and therefore need to be solved with two more independent equations.

The L2 model finds the two equations as follows:

$$T_{rad} = f_c T_f + (1 - f_c) T_s, \tag{8}$$

$$T_s - T_f = a(T_{rad} - T_a)^m, \tag{9}$$

where f_c is the fractional coverage of plant canopy, which can be obtained with field measurements and a and m are empirical coefficients determined from observations (Lhomme et al., 1994). A preliminary analysis of a and m values suggests that these parameters may vary with experimental data. However, approaches to adjust these parameters are not currently available so that the average values of $a = 0.1$ and $m = 2$ provided in Lhomme et al. (1994) were used for all data sets in this study.

N2 model uses the following two equations:

$$T_{rad}^4 = f_c T_f^4 + (1 - f_c) T_s^4, \tag{10}$$

$$\rho c_p \frac{T_f - T_{ac}}{r_f} = R_{nc}\left(1 - \alpha_{PT} f_g \frac{\Delta}{\Delta + \gamma}\right), \tag{11}$$

where R_{nc} is the part of the net radiation R_n above the canopy, α_{PT} is the Priestley–Taylor constant (1.26), f_g is the fraction of green leaf area in the total leaf area index, Δ is the slope of the saturation vapor pressure vs. temperature curve, and γ is the psychrometer constant. R_{nc} is computed from R_n with the following equation:

$$R_{nc} = R_n(1 - e^{\beta_R LAI}), \tag{12}$$

where β_R is the extinction coefficient of plant canopy with a value of -0.45 adopted for general plant covers (Norman et al., 1995). The original N2 model also gives estimates of the soil heat and latent heat fluxes of land surface. This study concerns only the sensible heat flux estimations.

OBSERVATIONAL DATA USED

Four data sets are used to compare the above models; FIFE, WG1, WG5, and WA. These data sets are obtained respectively from three interdisciplinary field experiments: FIFE'87, Monsoon '90, and Washita '92. General characteristics of these data sets and field experiments are listed in Table 2. More details are give below.

The FIFE Data Set

The FIFE data set were collected in tallgrass prairie sites near Manhattan, Kansas during the FIFE (Sellers et al., 1992). The vegetation is primarily grasses with deciduous trees located along stream channels. The topography is hilly with a valley to ridgetop height being typically 50 m and a distance between ridges on the order of 1 km. The remote sensing data used in this work were obtained with a helicopter-based remote sensing system during the 1987 campaigns (Walthal and Middleton, 1992). The data were acquired at approximately 300 m above ground level with Barnes Modular Multiband Radiometer (MMR) instrument as the helicopter hovered over a number of the surface flux stations in the study area. The field of view of the instrument is 1°, resulting in a nadir footprint of about 5 m in diameter. The radiometric surface temperature T_{rad} data were from Band 8 for the MMR instrument which has a nominal bandpass of 10.4–12.3 μm. Data acquired in IFC (Intensive Field Campaign) 1 in June, IFC 3 in July, and IFC 4 in October were used in this article. The approximate magnitude of atmospheric effects on T_{rad} measurements was evaluated by using near-simultaneous radiosonde profiles of atmospheric temperature and humidity (Brutsaert and Sugita, 1990). Analyses of data from four days (two days in IFC1 and one each in IFCs 3 and 4) gave a correction on the order of 0.3–0.4°C for the atmospheric effects to the T_{rad} from the MMR.

Table 2. The Three Field Experiments and the Four Data Sets

Experiment	*FIFE '87*	*Monsoon '90*		*Washita '92*
Data Set	FIFE	WG1	WG5	WA
Vegetation	Tallgrass prairie	Site 1: shrubs	Site 5: grasses	Grasses
Location	Kansas	Arizona	Arizona	Oklahoma
h_c (m)	0.10–0.70	0.80[a]	0.60[a]	0.30–0.65
LAI	0.30–3.55	0.40	0.80	0.86–2.33
f_c	0.22–0.63	0.26	0.40	0.50–0.98
Observ. period (day of year)	155–286	209–222	210–222	162–171
No. of observation	97	114	103	61
Mean of H (Wm^{-2})	138	132	132	181
SD of H (Wm^{-2})	92	59	49	55

[a] Apparent canopy height (see text).

The surface energy flux and meteorological measurements acquired at the different surface flux sites during the FIFE 1987 campaign are described in detail by Kanemasu et al. (1992) and Smith et al. (1992). The flux data and near surface meteorological data were reported at most stations at half-hourly intervals. The data used in this work were those reported for the half-hour intervals that most closely corresponded to the time of data acquisition by the helicopter-based remote sensing system. The near-surface meteorological data, including wind speed and air temperature, were acquired at various heights (from about 1.5–2.5 m) at different stations. The surface energy balance was estimated using Bowen ratio and eddy correlation techniques. Data from 13 of these surface flux sites were selected for this work. The variation in the amount of vegetation cover at these sites was mainly determined by whether the site was burned or unburned and grazed or ungrazed. Only two of the sites were unburned while the remaining sites were burned in the spring of the year. Only one site appeared to have significant topographic effects, having a slope of greater than 8°. The values of LAI ranged from about 0.3 to 3.55 and canopy height varied from approximately 10 cm to 70 cm.

The WG1 and WG5 Data Sets from Monsoon '90

The WG1 and WG5 data used in this work were collected in the Walnut Gulch Experimental Watershed near Tucson, Arizona during the Monsoon '90 field experiment (Kustas et al., 1991). The basin is about 1500 m above sea level with gently hilly topography dissected by ephemeral channels. Data were obtained in June 1990 during the dry season and late July and early August during the wet season or so-called "Monsoon" season where up to two thirds of the annual precipitation occurs between July and the end of September. The T_{rad} data in WG1 and WG5 were collected at two sites, one located with the shrub-dominated Lucky Hills subwatershed (Site 1) and the other with the grass-dominated Kendall subwatershed (Site 5). For details of the measurements see Norman et al. (1995). Both sites are heterogeneous having a wide range in vegetation cover, height, and architecture. The Lucky Hills site had about 26% vegetation cover with an *LAI* of around 0.4 and the average vegetation height of about 26 cm. For the Kendall site, there was about 40% vegetation cover with $LAI \approx 0.8$ and the average vegetation height of about 10 cm. For more details about the vegetation and LAI estimates, see Weltz et al. (1994) and Daughtry et al. (1991), respectively.

For both sites, Stannard et al. (1994) observed 1–3 m larger shrubs in height were present while stands of woody vegetation 3–5 m in height were located in nearby ephemeral channels. Micrometeorological techniques were used by Kustas et al. (1994) to determine d_{0m} for WG1 and WG5. The estimates for WG1 were $d_{0m} = 0.4$ m and $z_{0m} = 0.04$ m while for WG5 $d_{0m} = 0.3$ m and $z_{0m} = 0.01$ m. These estimates suggest that the larger shrubs present at both sites were significantly influencing tuberlent transport. Therefore, given the canopy cover was relatively sparse and open, it was assumed that $h_c = 2\ d_{0m}$, which yields an apparent canopy height of 0.8 m for WG1 and 0.6 m for WG5 listed in Table 2.

The surface energy balance was determined by eddy correlation, Bowen ratio, and variance (Tillman, 1972) techniques with measurements of net radiation and soil heat flux, and are described by Kustas et al. (1994) and Stannard et al. (1994). The flux and meteorological data were averaged over 20 min. The meteorological measurements were made at a normal height of 4 m above the ground surface.

The WA Data Set from Washita '92

The WA data set used in this study were collected during the Washita '92 field experiment conducted in the Little Washita River Basin near Chickasha, Oklahoma from 8 to 19 June 1992. The basin is approximately 610 km^2 in area and drains into the Washita river. The terrain is a mildly hilly mixture of rangeland, pasture, and cropland with smaller areas of forests, urban / highways, oil waste land, quarries, and reservoirs (Allen and Naney, 1991).

The data used here were collected at three Meteorological Stations (MS001, MS002, and MS003) in the Washita '92 experiment. They include Bowen-ratio, weather, and supplementary data, and radiometric measurements of surface temperature. For details of the measurements see Kustas et al. (1996). Station MS001 was located in a winter-wheat field that had been partially grazed and then allowed to revegetate. A single species of weed dominated and was interspersed with dead wheat plants. Total percent cover was estimated to be around 50% with average canopy height of about 55 cm and *LAI* of approximately 0.5. Station MS002 was located in a native pasture, densely vegetated with a mixture of grass and forbs. The average vegetation height was around 65 cm with *LAI* estimated to be about 2.3. Station MS003 was located in a winter-wheat field that had been fully grazed and then overtaken by weeds. Vegetation was fairly dense, and included many species of grasses and forbs with a mean canopy height of 30 cm and *LAI* of about 0.86.

The radiometric surface temperature data were acquired over as large and uniform an area as possible near the fetch area of each station with a 4-band radiometer mounted on a back-pack apparatus (yoke), and are described in Humes et al. (1993). The areas covered in each traverse with the yokes ranged from approximately 6300 m^2 near MS003 to 13,500 m^2 near MS002. Each traverse took about approximately 15–20 min, depending on the size of the area, and consisted of covering the area in a "forward" and "reverse" direction along a repeatable route. Approximately 10 data points were acquired along each 30 m of the traverse route. The traverses were done at a given site approximately every hour from the hours of about 9 a.m. to 5 p.m., weather permitting. The area averages of the measurements were used as the surface radiometric temperature.

MODEL PERFORMANCE

All models in Table 1 were run using the variable values of the observations in the above data sets to obtain predictions of the corresponding sensible heat fluxes. Constraints that $R_n > 100$ W m^{-2}, $T_r - R_a > 2°C$, and that $u > 1$ m S^{-1} were applied in using the above data sets, which guaranteed that the models were run under a well-developed unstable atmospheric surface layer and would reach a stable solution.

Model performance was quantitatively measured with the statistics of the difference between the model predictions and the field measurements of sensible heat fluxes. These statistics suggested by Willmott (1982) include the root mean square difference (RMSD), the mean absolute difference (MAD), the mean absolute percent difference (MAPD), and the index of agreement (*idx*). The purposes of these different statistics are also given in Willmott (1982). Table 3 has listed the formulas for computing these statistics. Also listed in Table 3 are the formulas for mean, standard deviation, and the coefficients of the linear regression between the model predictions and the field observations, which are used in the calculation of the above statistics.

All results of model performance presented below were obtained with the model parameters (s_{kB} of L1, a and β of L1, a and m of L2, a_{PT} and β_R of N2) set to be their average values from the literature. Several studies have observed the variations of these parameters with experimental data (e.g., Stewart et al., 1994; Troufleau et al., 1995; 1996; Lhomme et al., 1994). However, no methods to adjust these parameters *a priori* have been developed at this time except for the preliminary work by Troufleau et al. (1995). Therefore, only the average values for these model parameters from the literature were adopted in this study for the purpose of model intercomparison.

Figure 2 contains the plots of the model predictions versus field measurements of sensible heat flux H using all the data sets. The lines within the plots represent perfect agreement between the modeled and observed H. From the figure, one generally observes significant scatter between the predicted and measured H using most of the models. As shown in Figures 2a and 2b, the K1 model generally overestimated when measured $H < 150$ W m^{-2} and underestimated when measured $H > 150$ W m^{-2}, while the L1 model typically underestimated the measured values of H. The L2 model produced the largest number of outliers, even predicting negative H values as displayed in Figure 2c. In contrast, N2 model shows better agreement with the observations for most cases except when measured $H > 300$ W m^{-2}.

The quantitative measures of the model performance against the whole data set are listed in Table 4. From the table, the following conclusions can be made: 1) and L2 model has the largest MAD, MAPD, and RMSD and the smallest index of agreement (*idx*) and correlation coefficient (r), while the N2 model has the smallest MAD, MAPD, RMSD and the largest *idx* and r; 2) the single-source models K1 and L1 are similar in terms of the values of MAD, MAPD, RMSD, *idx*, and r. These quantitative results are consistent with the above qualitative findings about the performance of the models using Figure 2.

The performance of the models for different data sets is shown in Figures 3–6 and evaluated in Tables 5–8. For the data set from FIFE, the comparisons in Figures 3a and 3b for the two single-source models (K1 and L1) indicate that they compute significantly less variation in H than what was observed. In contrast, the predicted H-values in Figure 3 and 3d for the two

Table 3. Definition of the Quantitative Measures Used To Assess the Performance of the Models Estimating Sensible Heat Flux

Name	*Description*	*Mathematical Definition*
$\bar{P}$ or $\bar{O}$	Mean of all n modeled $H(P_i)$ or observed $H(O_i)$	$\bar{P}=\frac{1}{n}\sum_{i=1}^{n}P_i$ and $\bar{O}=\frac{1}{n}\sum_{i=1}^{n}O_i$
SD	Standard deviation of all P_i or O_i	$\left[\frac{1}{n-1}\sum_{i=1}^{n}(P_i-\bar{P})^2\right]^{1/2}$ or $\left[\frac{1}{n-1}\sum_{i=1}^{n}(O_i-\bar{O})^2\right]^{1/2}$
a	Intercept of the linear regression of P_i to O_i	$\bar{P}-b\bar{O}$
b	Slope of the linear regression of P_i to O_i	$\sum_{i=1}^{n}(P_i-\bar{P})(O_i-\bar{O}) \Big/ \sum_{i=1}^{n}(O_i-\bar{O})^2$
r	Linear correlation coefficient of P_i to O_i	$\sum_{i=1}^{n}(P_i-\bar{P})(O_i-\bar{O}) \Big/ \left[\sum_{i=1}^{n}(O_i-\bar{O})^2\sum_{i=1}^{n}(P_i-\bar{O})^2\right]^{1/2}$
MAD	Mean absolute difference of P_i to O_i	$\frac{1}{n}\sum_{i=1}^{n}\lvert P_i-O_i\rvert$
MAPD	Mean absolute percent difference of P_i to O_i	$\frac{100}{n}\sum_{i=1}^{n}\frac{\lvert P_i-O_i\rvert}{\bar{O}}$
RMSD	Root mean square difference of P_i to O_i	$\left[\frac{1}{n}\sum_{i=1}^{n}(P_i-O_i)^2\right]^{1/2}$
idx	Index of agreement of P_i to O_i	$1-\left[\sum_{i=1}^{n}(P_i-O_i)^2 \Big/ \sum_{i=1}^{n}(\lvert P_i-\bar{O}\rvert+\lvert O_i-\bar{O}\rvert)^2\right]$

dual-source models (L2 and N2) show significantly more variation. The single-source models (K1 and L1) tend to overestimate when the measured $H<100$ W m^{-2} and underestimate when the measured $H>200$ W m^{-2}. Although the predictions by the dual-source models, L2 and N2, gave greater scatter when compared to measured H, they tend to fall about the one-to-one line (see Figs. 3c–d. Accordingly, the predictions of the K1 and L1 models have larger MAD, MAPD, and RMSD and smaller agreement index (*idx*) and correlation coefficient (r) as shown in Table 5. Thus for the FIFE data, both dual-source models show better performance than the single-source models. The MAPD of the N2 model for the FIFE data is 34%, which may be acceptable given that at least a 20% variation in the sensible heat flux measurements can be expected (see Nie et al., 1992; Fritschen et al., 1992).

For the WG1 data set, Table 6 shows that the N2 model has the highest performance while the L2 model gave the lowest, although it still yielded acceptable results. The K1 model had similar values of MAD, MAPD, and RMSD, and r to the N2 model, but the value of *idx* for K1 is smaller. This is related to the significantly larger bias between predicted and measured H with the K1 model as revealed in the slope b and intercept a of the linear regression. From Figure 4a the K1 model can be seen to typically overestimate when the measured $H<100$ W m^{-2} and underestimate when the measured $H>200$ W m^{-2}. The values of MAPD of all models fall essentially between 20% and 30%, which is within the expected uncertainty of measured H using the various micrometeorological technique discussed in Kustas et al. (1994) and Stannard et al. (1994).

For the WG5 data set, the highest performance came from the predictions by the L1 model and the N2 model, which had the same value of *idx* (see Table 7). In fact, the L1 model had lower values of MAD, MAPD, and RMSD than the N2 model. The MAPD values of both the L1 model and N2 model are within the expected variations of the observations. The L2 model gave the lowest performance, having the smallest values for *idx* and r and the largest values for MAD, MAPD, and RMSD. This is mainly due to the L2 model having predictions of $H<0$ W m^{-2} for several sensible heat flux observations where $H>200$ W m^{-2} (see Fig. 5c). The K1 model's predictions were reasonable for observed H-values <200 W m^{-2}, but the model significantly underestimated the measurements of $H>200$ W m^{-2}. Therefore, the K1 model did not have as good an agreement with observations as the N2 and the L1 model.

Comparisons between model-derived and observed H for the WA data set are illustrated in Figure 6. The K1 model gave the best agreement with the measurements while the L2 model produced the highest values of MAD, MAPD,and RMSD (see Table 8). The L2 model predicted the variations in the magnitude of H across the field sites; thus it had a good correlation coefficient

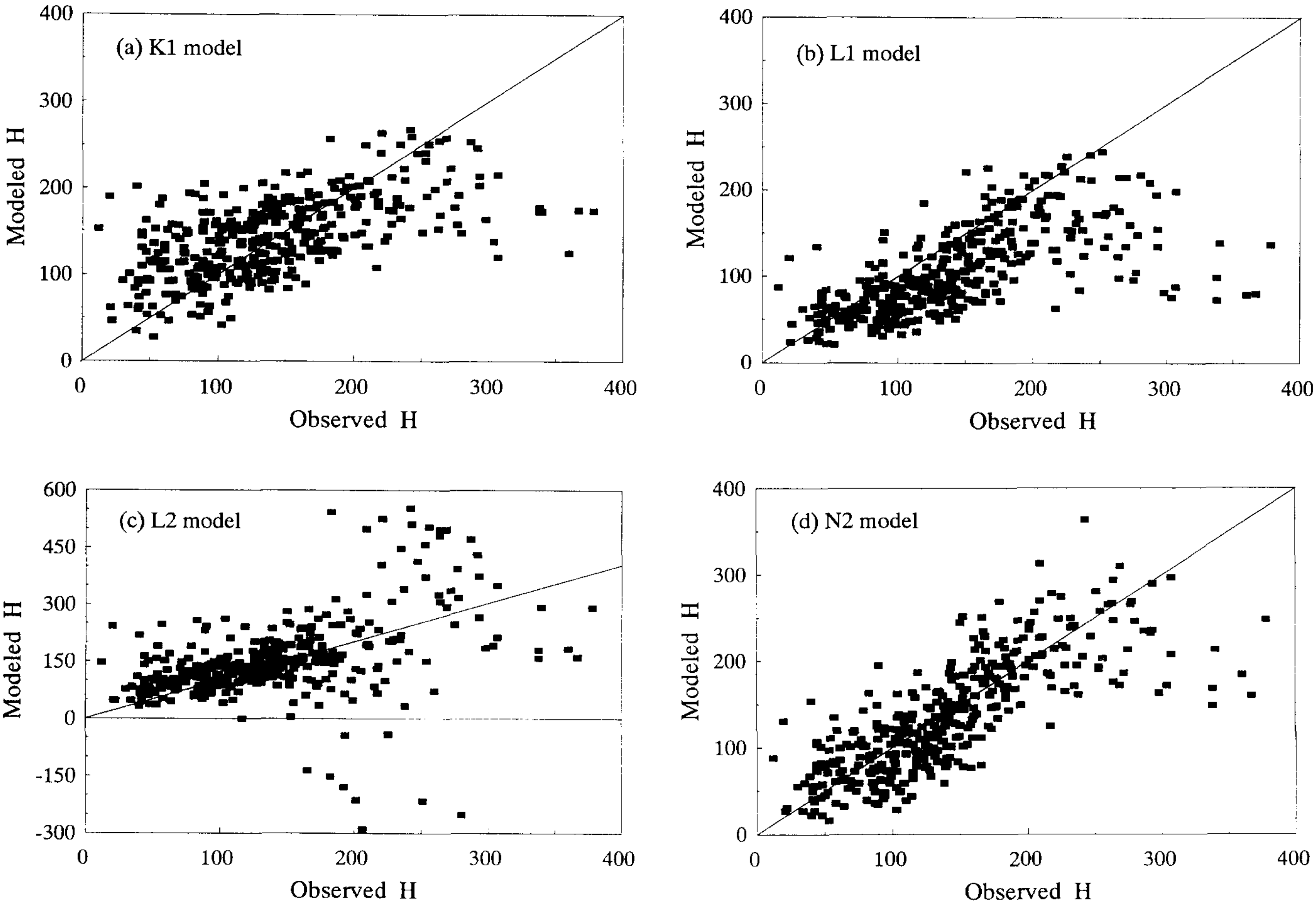

Figure 2. Modeled versus observed sensible heat flux H (W m^{-2}) for all data sets.

($r = 0.82$). However, it overestimated H significantly when the measured H 200 W m^{-2} (see Fig. 6c), such that it caused large values of the difference statistics to be computed. Except for the L2 model, the values of MAPD for all models are within the expected accuracy of these types of measurements (i.e., 20–30%).

SENSITIVITY ANALYSIS AND DISCUSSION

From the above model performance intercomparison, we have found that among the four models of sensible heat flux the N2 model had the best overall performance. The single-source models (K1 and L1) performed satisfactorily for some sites but usually produced bias estimates, especially for the FIFE and Monsoon '90 data sets. The dual-source models (L2 and N2) typically gave larger scatter between modeled and observed sensible heat fluxes but the estimates were significantly less biased. The question that is still unanswered is why some of these models performed better than others? In this section, we attempt to address this question by analyzing the sensitivities of these models to their common parameters and the parameters associated with a particular model.

The rationale for evaluating the model performance by analyzing the model sensitivity to the model parameters is that the value of the input variables and parameters used in the models for computing sensible heat flux contain a level of uncertainty. If the predictions of a model are too sensitive to the uncertainty in the values of particular variables or parameters, then significant differences between the predictions and the observations may result from inherent errors associated with estimating model variables or parameters.

In this analysis the sensitivity S_p of a model to a parameter p is defined as follows:

$$S_p = \left| \frac{H_- - H_+}{H_0} \right|, \tag{13}$$

where H_0, H_-, and H_+ are the sensible heat flux predicted by the model when the parameter equals its reference value p_0, $1.1p_0$, and $0.9p_0$, respectively, with reference values used for all other parameters. This sensitivity is actually the absolute value of the relative

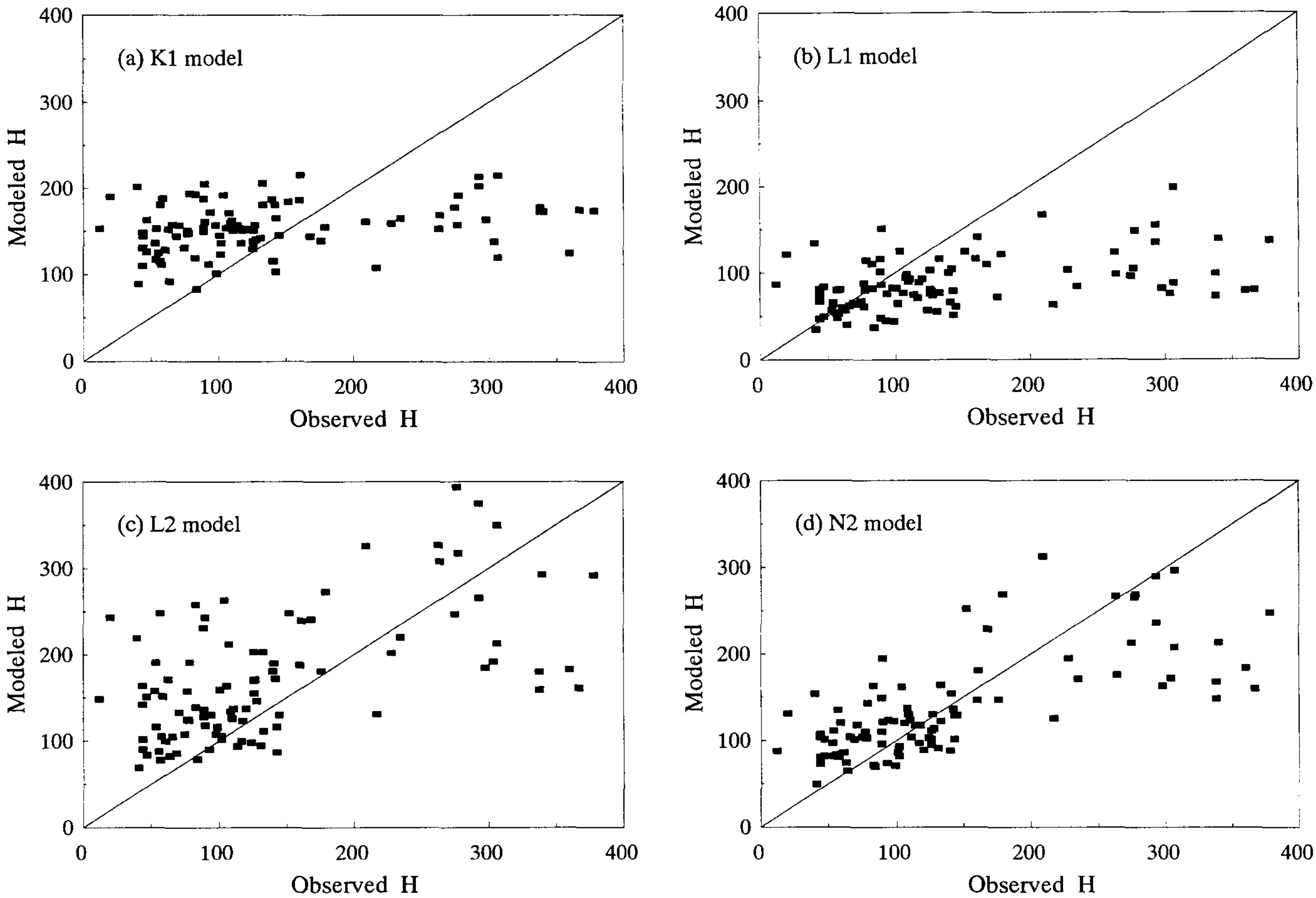

Figure 3. Modeled versus observed sensible heat flux H (W m^{-2}) for the FIFE data set.

change in the model predictions when the parameter changes $\pm$ 10% from its reference value. In other words, the sensitivity is the possible percentage "error" of the model predictions if the parameter value is uncertain within the $\pm$ 10% range of variation from its reference value. Thus, the larger the S_p value, the more sensitive the model is to the corresponding parameter.

All parameters or variables used in this sensitivity analysis are listed in Table 9. The reference values are generally their mean values from all data sets except the model parameters (sk_B, a, β, a, m, a_{PT}, and β_R), which were obtained from the references in Table 1. In the right most column of Table 9, the first two rows list the ranges for the roughness parameters (z_{0m} and d_{0m}) estimated as either a fraction of the canopy height or being prescribed from independent observations. For the observed variables (radiometric surface temperature T_{rad}, air temperature T_a, and wind speed u) and plant parameters (canopy height h_c, canopy fractional coverage f_c, leaf area index LAI, and leaf width s), the ranges cover their maximum and minimum values observed from the various data sets. The ranges for the model parameters (sk_B, a, β, a, m, a_{PT}, and β_R) were determined by obtaining a best fit between the modeled fluxes and the observations from the different data sets.

Values of S_p for the different models are listed in Table 10. Dashes indicate that the parameter is not used by the corresponding model. From the S_p-values, the models show larger sensitivity to the instrument-measured variables (T_{rad} and T_a) compared to the other parameters. This confirms that the models are mainly driven by these input variables. Values of the meteorological variables from the data sets were obtained with instruments which probably have uncertainties of less than 10%. However, a 10% uncertainty in T_{rad} from satellite observations is probably not atypical (Schmugge et al., 1993).

In Table 10, the S_p-value for surface roughness z_{0m} is essentially 0 for the N2 model. In contrast, the other three models, especially L1, are to some degree sensitive to z_{0m}. Surface roughness is one of the parameters not easily determined for heterogeneous landscapes. Thus, minimizing the sensitivity of the model to z_{0m}, such as with the N2 model, has significant advantages for modeling sensible heat flux over complex surfaces. The uncertainty in z_{0m} for heterogeneous surfaces is typically

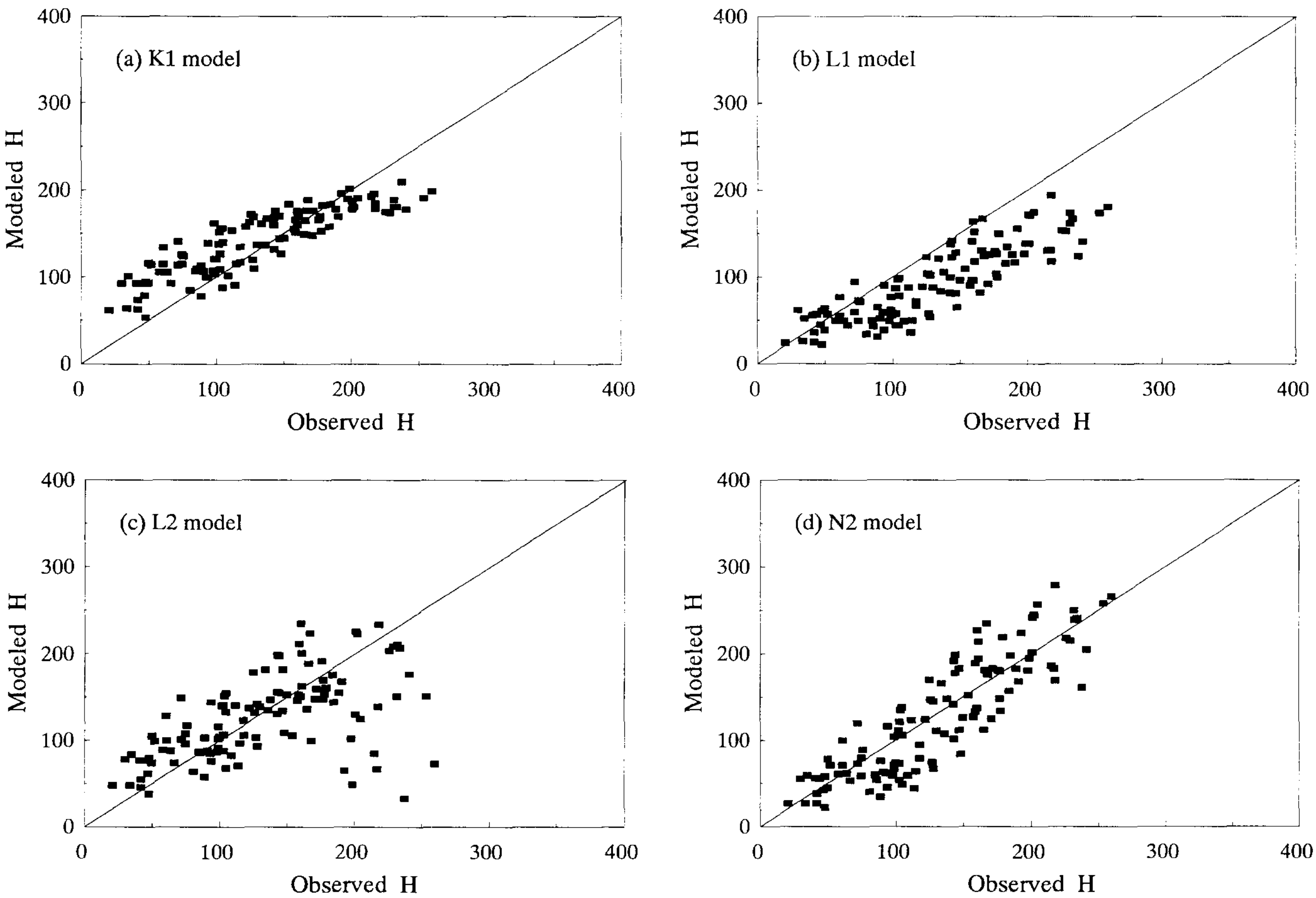

Figure 4. Modeled versus observed sensible heat flux H (W m^{-2}) for the Monsoon '90 site 1 data set WG1.

greater than 50%. Taking the extreme of a $\pm$ 90% uncertainty in z_{0m} from its reference value, the S_p-value increases to 0.74, 0.97, 0.67, and 0.12 for the K1, L1, L2, and N2 models, respectively. This indicates that all models show a significant increase in the S_p-value due to a more realistic uncertainty in z_{0m}. However, the N2 model still has relatively low sensitivity to this parameter.

For zero-plane displacement d_{0m}, the S_p-values in Table 10 indicate that the single-source models are less sensitive than the dual-source models with the L2 model showing the largest sensitivity. Since d_{0m} is another parameter which is difficult to determine, the high sensitivity of the L2 model to this parameter may be a serious limitation and one of the reasons for the generally large scatter observed for the L2 model. For the N2 model, d_{0m} is also of some significance, and may have to be chosen carefully for heterogeneous surfaces.

The single-source models (K1 and L1) were not affected by plant parameters (h_c, f_c, LAI, s and f_g) as shown in Table 10 because these models currently do not use them. If the parameters of these models (s_{kB}, α, and β, respectively) can be adjusted with the plant parameters as attempted by Troufleau et al. (1995), they may be able to account for the effects of vegetation indirectly. The dual-source models (L2 and N2) separate the different contributions of plants and soil to the surface sensible heat flux, and therefore consider the effects of the plant parameters. Although by more realistically treating the surface as a two-component or dual-source system one would expect more accurate simulations of the surface sensible heat flux, these plant parameters are also difficult to determine over heterogeneous surfaces. In the data sets used in the last section, these plant parameters were derived from visual observations, some area samples or indirectly from measurements of biomass or plant species type. These measurements are highly variable in space and thus contain a significant degree of uncertainty. Therefore, the higher sensitivities of the L2 model to these parameters shown in Table 10 may imply higher probability that its predictions of H will deviate from the observations. Thus, even though the dual-source models more realistically represent the sources of H, their sensitivity to plant and soil parameters may make them difficult to apply operationally. Fortunately, the N2 model appears less sensitive to these plant parameters, which results in predictions of H being more constrained when the parameters are not correctly specified. This may be an-

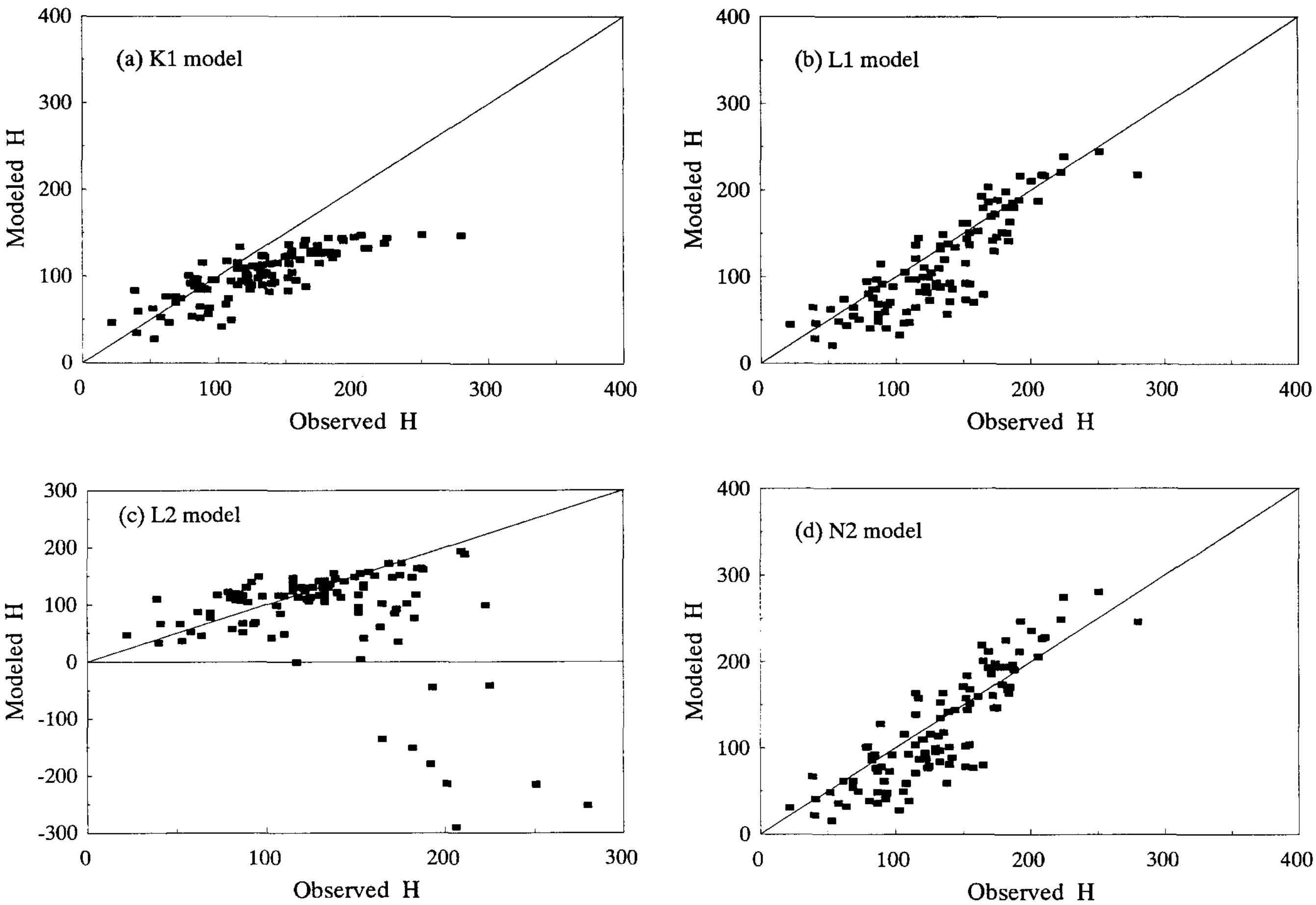

Figure 5. Modeled versus observed sensible heat flux H (W m^{-2}) for the Monsoon '90 site 5 data set WG5.

other attribute of the N2 model that results in the model-derived fluxes being in satisfactory agreement with the observations.

The parameter s_{kB} had significant impact on the K1 model estimates of H as shown by the S_p-value in Table 10. Thus, the specification of the value of s_{kB} is critical in how well the K1 model performs. Kustas et al. (1995) had to use different values of s_{kB} for the different observation periods with the FIFE data in order to obtain satisfactory results. They found that the value of s_{kB} had to be doubled to 0.30 for IFC 1 and IFC 3 observations while s_{kB} had to be reduced to 0.05 for IFC 4 in order to remove most of the bias in the model predictions and have results comparable to the N2 model. They further found that the value of s_{kB} appears to be dependent on the magnitude of sensible heat flux itself. The values of s_{kB} determined with the data sets used in the present study varied from 0.10 for the WG5 data to 0.36 for the FIFE data. Troufleau et al. (1996) also observed this dependency and showed analytically its possible dependence on the magnitude of H. Lack of *a priori* knowledge of the value of s_{kB} and given the level of uncertainty in estimating z_{0m}, it may be difficult to improve the performance of the K1 model.

The values of S_p in Table 10 indicate a large sensitivity of the L1 model to the value of α while the sensitivity to β is negligible. The α and β values that give the smallest root mean square difference (RMSD) between model predictions and observations for the different data sets were also computed. As listed in Table 9, the α-value obtained ranges from 0.56 for the Washita '92 Site 3 data to 0.80 for Washita '92 Site 1 data. The β-value ranges from -0.6 for the WG5 data set to -0.15 for the Washita '92 site 1 data. Troufleau et al. (1995) showed that α may vary from 0.40 to 0.79 when $\beta = 0$. This degree of variability in the model parameters, especially α, for the different data sets and the sensitivity of the model to the value of α (see Table 10) will require a method to estimate its value *a priori* in order to improve the performance of the L1 model.

The L2 model shows high sensitivity to α and m parameters (see Table 10). When the L2 model is fitted to the different data sets with $m = 2$, the value of a changed from 0.07 for the WG1 data set to 0.27 for the Washita '92 Site 2 data. This variation range of a is listed in Table 10. Thus, there appears to be fairly large variability in this parameter, which may be another factor in causing some of the larger scatter observed

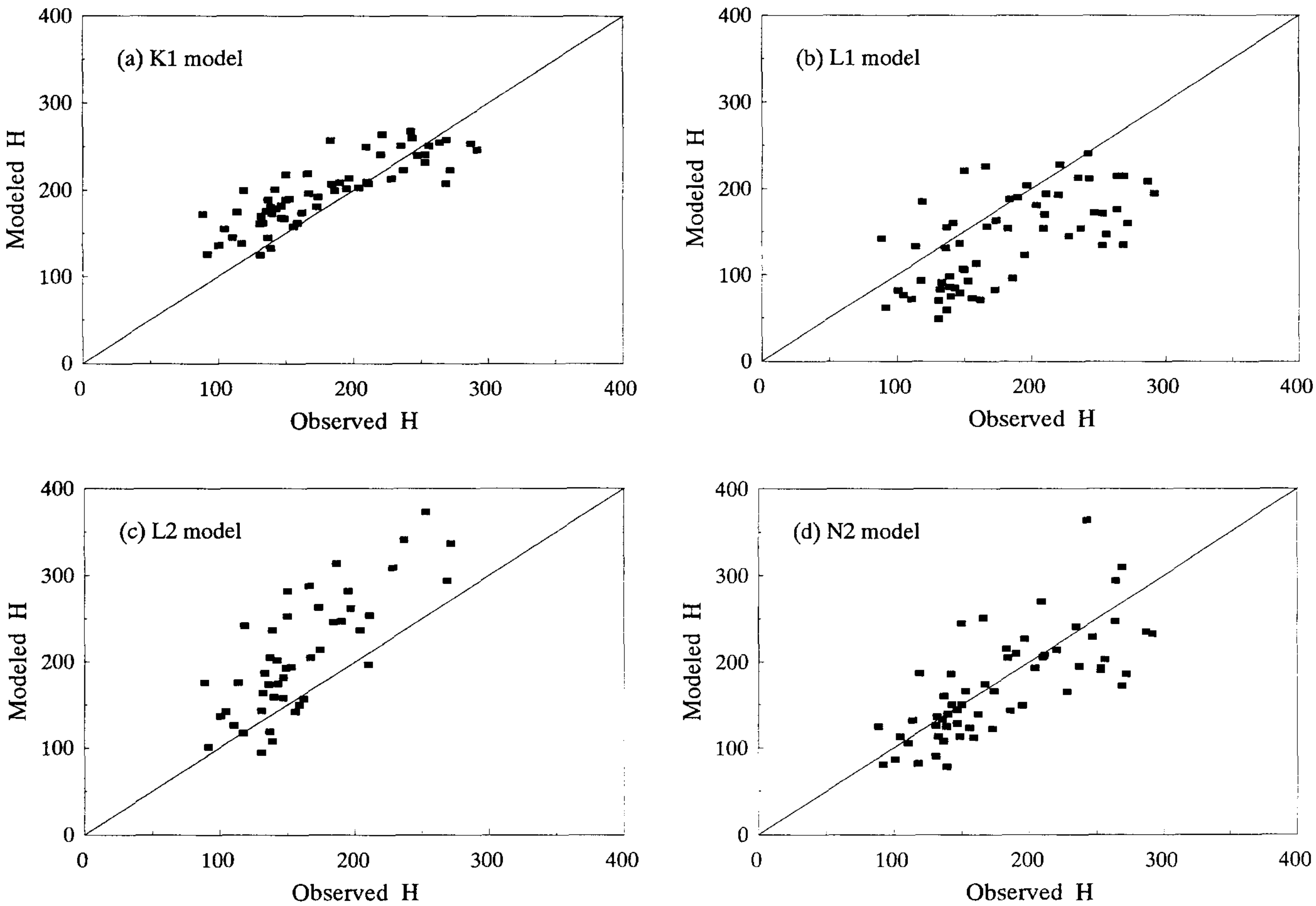

Figure 6. Modeled versus observed sensible heat flux H (W m^{-2}) for the Washita'92 data WA.

between the L2 model estimates of H and the observations.

The N2 model has three parameters: the fraction of "green" leaves (actually transpiring) f_g, the Priestly–Taylor coefficient α_{PT}, and the extinction coefficient of net radiation through plant canopy β_R. The S_p-values of the N2 model to all of these three parameters are smaller than the S_p-values of the other models to their key parameters. This smaller sensitivity may indicate an advantage of the N2 model in predicting H over heterogeneous surfaces. However, the best fit values of α_{PT} and β_R for the different data sets used in this study also had significant variations. The α_{PT}-value varied from 1.00 for the Washita '92 Site 2 data to 1.44 for the FIFE data set. The range for β_R is from -0.32 for the Washita '92 Site 2 data to -0.71 for the WG1 data set. Moreover, f_g is difficult to determine operationally. The sensitivity of the N2 model to f_g indicates that the performance of the N2 model in predicting H is dependent to some degree on how well we know the physiological condition of the vegetation in order to estimate the appropriate value of f_g.

The above analysis method can be justified for comparing the sensitivity of different models to the same parameter. However, since the uncertainty of a parameter value for a given surface may be smaller or larger than the $\pm$ 10% range of variation from its reference value assumed in this analysis, the resulting S_p-value may not have the same meaning for different parameters. Thus, when one compares the sensitivity of one model to a parameter $p1$ and the sensitivity of another model to another parameter $p2$, one needs to consider the difference in the uncertainty of the parameter estimates. One possible way to consider this is to recompute the S_p-values by using Eq. (13) with the H_- and H_+ being the model outputs of sensible heat flux corresponding to the minimum and maximum values of the parameters, respectively. This approach was used to recalculate the S_p-values for the parameters specifically associated with each model. The model specific parameters are listed in Table 11. The minimum and maximum possible values of the model parameters are from Table 9. The results in Table 11 indicate that the N2 model is generally less sensitive to its model specific parameters compared to the other models. In fact, except for f_g, the model sensitivity is close to the uncertainty in measurement of H (i.e., $\pm$ 20%).

The above results are dependent on the magnitude of the reference values for the model parameters in the sensitivity calculations. In other words, the S_p-values

Table 4. Quantitative Measures of Model Performance for All Data Sets

Model	$\bar{P}$ ($W\ m^{-2}$)	SD ($W\ m^{-2}$)	a ($W\ m^{-2}$)	b	r	MAD ($W\ m^{-2}$)	MAPD (%)	RMSD ($W\ m^{-2}$)	*idx*
K1	144	46	88	0.40	0.59	42	29	56	0.73
L1	106	50	40	0.47	0.64	44	31	64	0.72
L2	151	106	57	0.67	0.43	61	43	99	0.62
N2	137	69	29	0.77	0.76	34	24	47	0.87

Table 5. Quantitative Measures of Model Performance for the FIFE Data

Model	$\bar{P}$ ($W\ m^{-2}$)	SD ($W\ m^{-2}$)	a ($W\ m^{-2}$)	b	r	MAD ($W\ m^{-2}$)	MAPD (%)	RMSD ($W\ m^{-2}$)	*idx*
K1	154	30	142	0.09	0.27	75	54	90	0.42
L1	87	31	67	0.15	0.43	66	48	97	0.50
L2	172	73	110	0.45	0.57	67	49	85	0.72
N2	138	59	75	0.45	0.71	47	34	65	0.79

may change significantly for a particular model parameter if the reference value is changed. For example, if the reference value of f_g changes from 0.5 to 0.9, then the S_p-value in Table 10 for the N2 model would increase from 0.07 to 0.19. This suggests that the S_p-values listed in Tables 10 and 11 probably provide order of magnitude assessments of model sensitivity to the various parameters.

We examined the factors which may have caused the negative H-values predicted by the L2 model. Figure 7 shows the response of all the models to changes in surface-air temperature differences. From the figure, we can see that the negative predictions of L2 result from surface–air temperature difference greater than 20°C. The factor(s) which cause(s) the prediction of negative H from L2 can be seen by combining Eqs. (7)–(9) yielding

$$H = \rho c_p \frac{(T_{rad} - T_a) - c\left[a(T_{rad} - T_a)^m\right]}{r_a + r_e}, \tag{14}$$

Table 6. Quantitative Measures of Model Performance for the WG1 Data Set from Monsoon '90 Site 1

Model	$\bar{P}$ ($W\ m^{-2}$)	SD ($W\ m^{-2}$)	a ($W\ m^{-2}$)	b	r	MAD ($W\ m^{-2}$)	MAPD (%)	RMSD ($W\ m^{-2}$)	*idx*
K1	142	38	69	0.56	0.87	27	21	33	0.87
L1	94	43	10	0.64	0.86	40	31	48	0.80
L2	126	49	66	0.46	0.55	36	28	52	0.75
N2	127	67	−5	1.00	0.87	27	20	33	0.93

Table 7. Quantitative Measures of Model Performance for the WG5 Data Set from Monsoon '90 Site 5

Model	$\bar{P}$ ($W\ m^{-2}$)	SD ($W\ m^{-2}$)	a ($W\ m^{-2}$)	b	r	MAD ($W\ m^{-2}$)	MAPD (%)	RMSD ($W\ m^{-2}$)	*idx*
K1	103	29	38	0.49	0.83	34	26	41	0.75
L1	115	55	−13	0.97	0.86	25	19	33	0.90
L2	86	+1	157	−0.54	−0.29	62	47	124	0.23
N2	122	+6	−30	1.15	0.87	28	21	34	0.90

Table 8. Quantitative Measures of Model Performance for the WA Data Set from Washita '92

Model	$\bar{P}$ ($W\ m^{-2}$)	SD ($W\ m^{-2}$)	a ($W\ m^{-2}$)	b	r	MAD ($W\ m^{-2}$)	MAPD (%)	RMSD ($W\ m^{-2}$)	*idx*
K1	200	39	90	0.60	0.85	28	16	35	0.86
L1	141	53	28	0.62	0.65	51	28	61	0.71
L2	275	135	−92	2.03	0.82	98	54	133	0.59
N2	181	76	14	0.92	0.67	39	21	56	0.79

Table 9. Parameters or Variables Used in the Sensitivity Analysis

Parameter	*Units*	*Reference Value*	*Range in Data*
z_{0m}	m	0.06	0.003–0.07
d_{0m}	m	0.39	0.02–0.467
T_{rad}	°C	34.0	18.2–51.1
T_a	°C	26.0	10.9–34.4
u	m/s	4.0	1.0–9.4
h_c	m	0.6	0.30–0.80
f_c	–	0.39	0.22–0.98
LAI	–	1.0	0.30–3.55
s	m	0.005	0.005–0.02
s_{kB}	s/m/°C	0.15	0.05–0.30
α	°C	0.8	0.56–0.80
β	–	−0.5	−0.6 to −0.15
a	°C^{-m}	0.1	0.07–0.27
m	–	2.0	1–2
f_g	–	0.5	0.10–1.0
α_{PT}	–	1.26	1.00–1.44
β_R	–	−0.45	−0.32 to −0.71

where r_e is an equivalent resistance of r_s and r_f in parallel and c is a combination of f_c, r_f, and r_s [see Lhomme et al. (1994 for details]. The second term in the numerator of Eq. (14) is a nonlinear function of $T_{rad} - T_a$), which may increase faster than the first term and, as a result compute a negative H-value when $(T_{rad} - T_a)$ increases. Therefore, to improve the performance of the L2 model, it may be necessary to modify Eq. (9) in order to avoid the prediction of negative H under obviously highly convected conditions.

SUMMARY AND CONCLUSIONS

Using the observational data from the three interdisciplinary field experiments, the performance of four models in predicting land surface sensible heat flux adopting average values of model parameters was evaluated. By analyzing the sensitivity of the models to common parameters and input variables, reasons for differences in the performance of the models and the potential to improve the agreement with observations could be ascertained. The following conclusions have been drawn from this analysis:

Table 10. S_p Values of the Four Models with ± 10% Range of Variation in the Parameters or Variables from Their Reference Values

Parameter	*K1*	*L1*	*L2*	*N2*
z_{0m}	0.07	0.10	0.06	0.00[a]
d_{0m}	0.01	0.00[a]	0.11	0.05
T_{rad}	0.41	0.71	0.54	0.52
T_a	0.33	0.56	0.44	0.43
u	0.03	0.14	0.07	0.06
h_c	–	–	0.14	0.07
f_c	–	–	0.10	0.04
LAI	–	–	0.11	0.07
s	–	–	0.02	0.01
s_{kB}	0.13	–	–	–
α	–	0.67	–	–
β	–	0.05	–	–
a	–	–	0.11	–
m	–	–	0.52	–
f_g	–	–	–	0.07
α_{PT}	–	–	–	0.08
β_R	–	–	–	0.07

[a] The value is less than 0.005.

Table 11. Values of S_p of the Four Models Using the Full Range of Variation in Model Specific Parameters

Parameter	*K1*	*L1*	*L2*	*N2*
s_{kB}	1.11	–	–	–
α	–	1.07	–	–
β	–	0.23	–	–
a	–	–	1.21	–
m	–	–	0.53	–
f_g	–	–	–	0.80
α_{PT}	–	–	–	0.27
β_R	–	–	–	0.14

1. From the comparisons of modeled versus measured sensible heat flux for the different surfaces, the dual-source model N2 had the best agreement with its MAPD values being similar to the observational accuracy (i.e. ~ 20%). Furthermore, from the sensitivity analysis it appears to have the greatest potential for operational applications since it is not very sensitive to the uncertainty in the estimates of most parameters.
2. Single-source models (K1 and L1) rely heavily on the specification of the surface roughness z_{0m} and empirical relationships in accounting for differences between aerodynamic and radiometric temperature. Therefore, it may be difficult to improve their performance without some independent means of estimating the empirical coefficients and a reliable method for determining z_{0m}.
3. Estimates from the L2 model tend to produce the largest scatter with the observations. This may be related to the fact that the L2 model is more sensitive to variations in most of the parameters common in dual-source models. In addition, its response to high surface-air temperature differences in the sensitivity analysis differs from all other models (see Fig. 7). Therefore, it may be more difficult to obtain reliable estimates for the L2 model on an operational basis.

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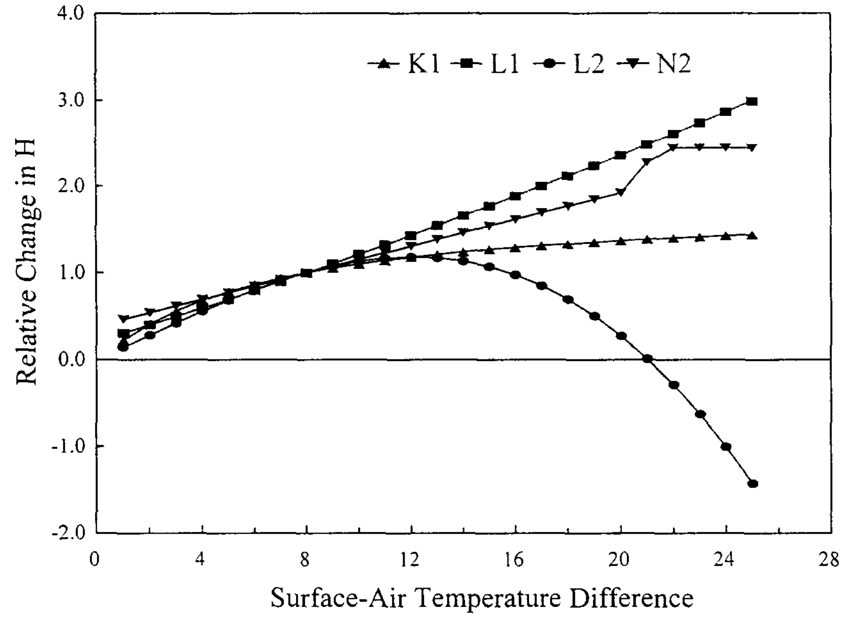

Figure 7. The relative changes in sensible heat flux predicted by the models in response to changes in surface-air temperature difference (°C).

experiment possible. In addition, we would like to thank the personnel at the USDA-ARS Little Washita River Watershed Field Office in Chickasha for handling much of the logistics during the field campaign. Processing of the yoke data for Monsoon '90 was performed by T. R. Clarke and M. S. Moran from the USDA-ARS U.S. Water Conservation Lab, Phoenix, Arizona. The continuous measurements of soil and vegetation temperatures for Monsoon '90 were collected and processed by W. D. Nichols from the USGS-Water Resources Division, Carson City, Nevada. The authors also acknowledge D. I. Stannard from the U.S. Geological Survey, Denver, Colorado and J. H. Blanford, affiliated with the University of Arizona during Monsoon '90, who were mainly responsible for the Monsoon '90 surface flux data. The authors are indebted to D. I. Stannard, who collected and processed the surface flux measurements made during Washita '92. Funding from NASA Interdisciplinary Research Program in Earth Science (NASA Reference No. IDP-88-086) and funds from USDA-ARS Beltsville Area Office provided the necessary financial support to conduct the Monsoon '90 field study. The authors are also indebted to many individuals who participated in the planning and implementation of the FIFE experiment, among them: F. G. Hall (NASA), P. J. Sellers (NASA), and R. E. Murphy (NASA); the team responsible for acquiring and analyzing the helicopter-based remotely sensed data, led by C. Walthall (University of Maryland); the FIFE Information System team, led by D. E. Strebel of Versar, Inc.; and the researchers responsible for the surface flux measurements used in this analysis, including E. A. Smith, L. J. Fritschen, E. T. Kanemasu, W. J. Shuttleworth, J. B. Stewart, S. B. Verma, W. L. Crosson, H. L. Weaver, M. L. Wesley, and R. T. Field. Finally, the authors are indebted to the helpful comments from two anonymous reviewers and from K. E. Kunkel and J. M. Norman on an earlier version of this manuscript.

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